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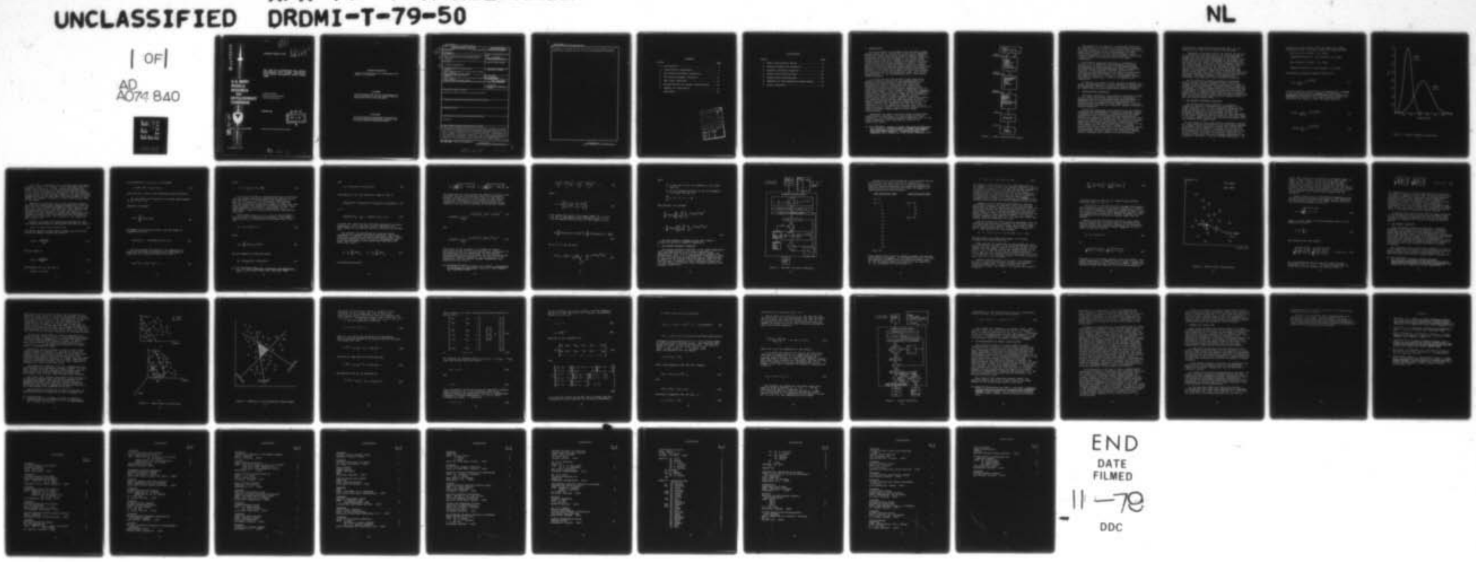

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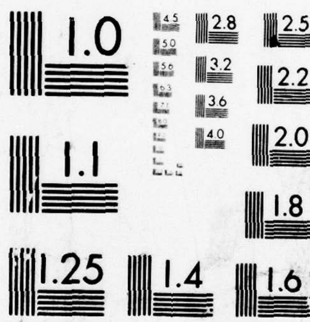

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TECHNICAL REPORT T-79-50

THE USE OF CLASSIFIERS AND MICROPROCESSORS FOR TARGET IDENTIFICATION USING MILLIMETER WAVE SIGNATURES

U.S. ARMY MISSILE RESEARCH AND DEVELOPMENT COMMAND

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26 APRIL 1979

Redstone Arsenal, Alabama 35809

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The problem of implementing three basic classification techniques for target acquisition in millimeter wave guided weapon systems is discussed in this report. The three classifiers are (1) the maximum likelihood classifier (2) the nearest neighbor classifier and (3) the linear classifier. The mathematics of each classifier is explicitly delineated in order to assess memory storage and computation load requirements. Using these results, the applicability of microprocessors for implementing these classifiers into fieldable systems is

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considered. It is shown that the classifiers are easily adaptable to experimental target signatures and that the use of microprocessors is requisite.

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1. INTRODUCTION

The effectiveness of millimeter wave (mm-wave) guided weapon systems may be limited by the ability to adequately perform the target acquisition function. Present mm-wave technology provides for the detection of moving targets in clutter and of stationary targets in low clutter. Only limited classification is currently attainable; basically, classification with mm-wave sensors is limited to moving versus stationary targets and ground versus air targets. There is a need for a mm-wave target acquisition system that provides for the detection of both moving and stationary targets in all clutter environments and that also provides for classification to the recognition level, with further classification to the identification level (IFF) being highly desirable.

It is believed that the desired target acquisition capability may be achieved via the implementation of a multiple discriminant system. Multiple discriminant processing is based on the premise that effective classification can be achieved by the logical and/or statistical processing of reasonably independent sets of radar discriminants. Such a system, is depicted in Figure 1. A millimeter radar is used to obtain returns dependent on target/clutter characteristics. These are then processed, usually with respect to time, to produce derived discriminants such as doppler spectra, cross polarization, etc. These discriminants are then processed to obtain numbers representing the physical characteristics of the target, such as size, velocity, etc. The job of the classifier is (1) to compare the features with those of training targets stored in the classifier memory, and (2) to reach a decision, ideally based on exact target identification.

Dasarathy[1] has made a simulation study of three basic classification techniques: (1) the maximum likelihood classifier; (2) the nearest neighbor classifier, and (3) the linear classifier. Each technique was shown to be potentially useful.

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1. B.V. Dasarathy, TARECS: A Target Recognition System for Identification of Land Targets in Combat Environments Using Millimeter Sensors - A Simulation Study, M&S Computing, Inc., Report No. T-CR- 78-20, September 1978.

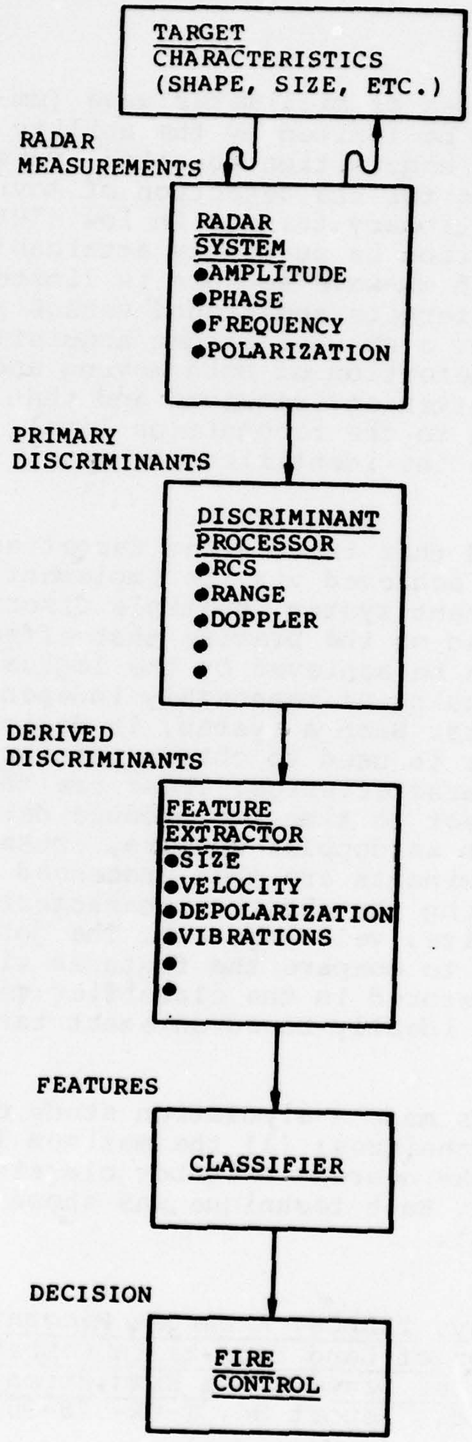

Figure 1. Radar classification system.

The purpose of this report is to delineate explicitly the implementation of these three classification techniques for radar systems for target classification and, further, to assess the applicability of microprocessors to these classifiers. Section 2 of this report presents a brief review of nomenclature relating to classifiers, after which a report section is devoted to each of the three classifiers.

The maximum likelihood classifier is presented in Section 3; it is shown that the assumption of Gaussian distributions of features results in low memory storage requirements and small computational loads. In Section 4, the basic nearest neighbor technique is shown to be simplistic in implementation but it results in high memory and computational requirements. The linear classifier, discussed in Section 5, is found to lie somewhere between the previous classifiers in terms of assumptions and computation.

In Section 6 an effort is made, through an example, to assess the implementation of each classifier using available microprocessors. Section 7 presents an overall summary of the report and gives conclusions drawn from the analysis.

2. CLASSIFICATION TECHNIQUES

The three statistical classification techniques studied in this report use pattern recognition or statistical hypothesis testing in algorithms which lend themselves to implementation in field system mircroprocessors. The computing power and memory storage capabilities of current microprocessor chips are well suited for complex analyses of target signatures.

Statistical techniques can be divided into two classes: parametric and nonparametric. Parametric techniques require a knowledge of the probability distribution of the target signature and that this distribution be mathematically defined. For example, consider the radar cross section (RCS) of a given target. The RCS measured is a function of aspect angle, and the observed aspect angle (under battlefield conditions) will have some probability distribution. If one could measure the RCS of various targets in a combat scenario and obtain enough data, the RCS probability density of each target class could be plotted and a mathematical representation be found. Ideally, the probability density would be mathematically simple, such as the Gaussian

distribution. Experimental data indicate that, for the example of RCS, this is not likely to be the case.

Parametric techniques lead to the highest reliability of classification but also require the most knowledge of targets and that the knowledge result in well-defined probability distributions. Nonparametric techniques, which do not specifically require knowledge of the probability distributions, are useful when target signature statistics are highly complex or cannot be reliably defined. This is the situation most likely in the real world. Given an initial set of training data for which the targets are labeled, a nonparametric algorithm determines the most likely target type for a given input. It should be mentioned that error analysis (decision reliability) is possible for parametric techniques, whereas, for nonparametric techniques, only empirical error analysis is feasible.

Use of statistical pattern recognition techniques usually implies that the fundamental data is directly related to identifiable physical characteristics. There is another class of techniques, syntactic pattern recognition techniques, in which a target signature is broken down into a combination of substructures or primitives for which the relationships to physical characteristics are not readily apparent. For an unknown target, the classifier searches for these substructures and uses algorithms (grammar rules) to test for various target types.

3. THE MAXIMUM LIKELIHOOD CLASSIFIER

The maximum likelihood classifier, or Bayesian classifier, requires a probabilistic description of the target signature, i.e., it is a parametric technique. Any target signature which is aspect angle dependent can in principle be applied to this technique, so that the probability distribution contains both the angle dependence of the target signature and the probability of aspect angle. In practice, complex targets will not have signatures which vary smoothly with aspect angle.

As an example of this classification technique, consider the radial velocity distribution of moving targets obtained from doppler shift frequencies. Assume that a sufficient quantity of training data is available and that the data fortuitously can be fitted by a Gaussian distribution. Use of the Gaussian (or Normal) distribution simplifies the analysis, because the data are completely described by two parameters, the mean, μ , and the standard deviation, σ . We

consider two target types, tanks and jeeps, with tanks moving more slowly than jeeps. Assume the following data:

Mean velocity of tanks = μ_T = 16 mph

Standard deviation of tank velocity = σ_T = 5 mph

Mean velocity of jeeps = μ_J = 35 mph

Standard deviation of jeep velocity = σ_J = 10 mph

The Gaussian probability density function is

$$p(v) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-(v-\mu)^2/2\sigma^2} , \qquad (1)$$

and this function is plotted for the assumed data in <u>Figure 2</u>. The functions plotted in <u>Figure 2</u> are known as <u>a posteriori</u> conditional probability densities, because they indicate the probability of a target velocity being $\leq v$, given that the target is known. We denote these by

$$p(v/T) = \frac{1}{\sqrt{2\pi}\,\sigma_T} e^{-(v-\mu_T)^2/2\sigma_T^2} , \qquad (2)$$

$$p(v/J) = \frac{1}{\sqrt{2\pi}\,\sigma_J} e^{-(v-\mu_J)^2/2\sigma_J^2} . \qquad (3)$$

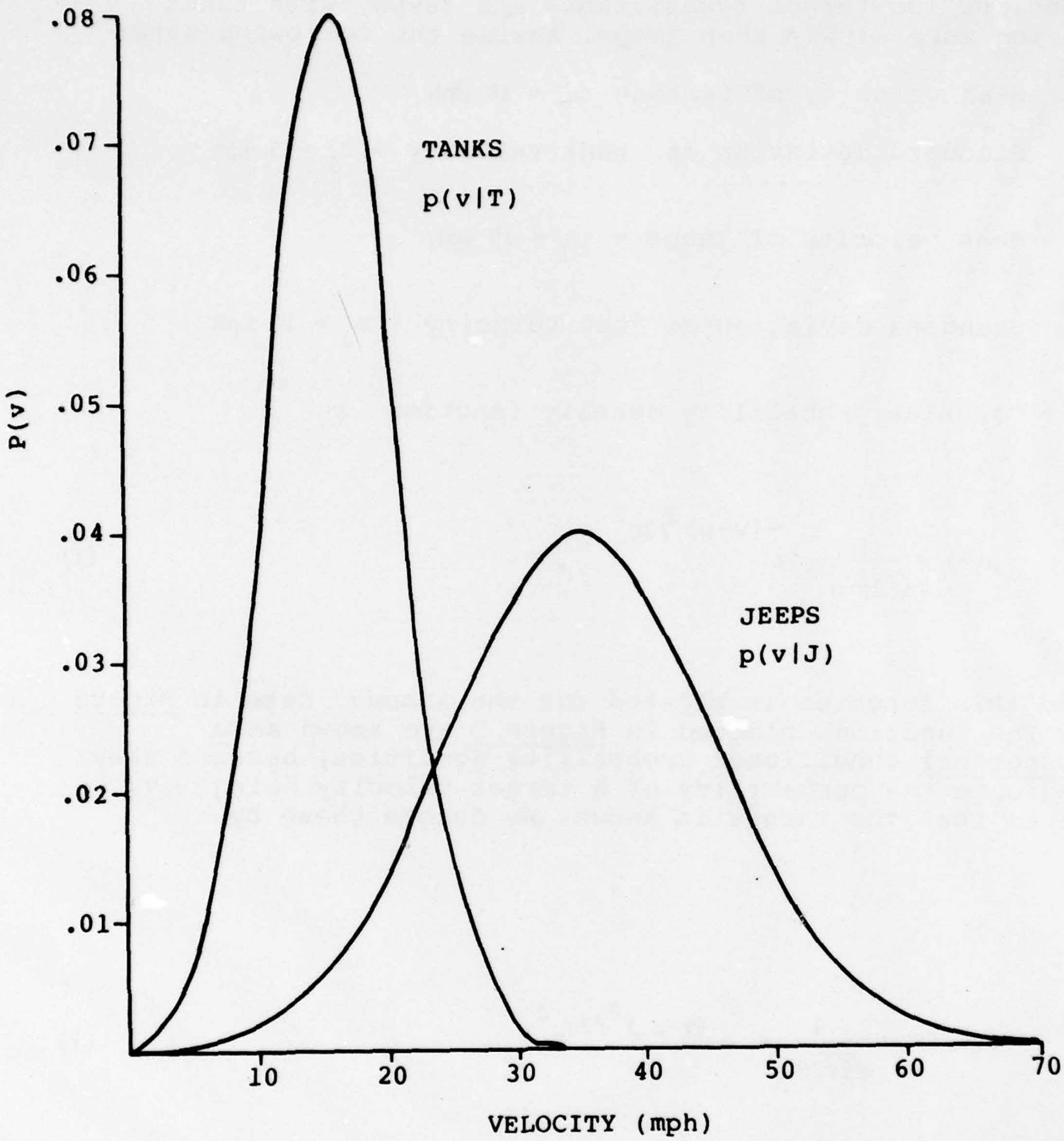

Figure 2. Velocity probability densities.

If we take a measurement on an unknown target and obtain velocity v (here v is a number - not a variable), what we would like to know is: (1) the conditional probability, $P(T/v)$, that the target is a tank, given that the velocity is v, and (2) the conditional probability that the target is a jeep, $P(J/v)$, given that the velocity is v. Based on these probabilities, we can then make a decision whether to fire a weapon. For example, if $P(T/v) > P(J,v)$, then we will shoot at the target.

Additional information that we get from the training data are the unconditional a priori probabilities, $P(T)$ and $P(J)$. $P(T)$ is the probability that any given target in the field is a tank; $P(J)$ is the same for a jeep. (We maintain the simplification that there are only two types of targets.) For this example, we assume that the average ratio of tanks to jeeps in all the battles we have monitored is three to one. Thus $P(T) = .75$, and $P(J) = .25$. [Note that $P(T) + P(J) = 1$.]

Finally, we define the unconditional probability that any velocity measurement we make yields the value v; this is

$$p(v) = p(v/T)\,P(T) + p(v/J)\,P(J). \tag{4}$$

The Bayes' Theorem is then used to compute the $P(T/v)$ and $P(J/v)$. The Bayes' Theorem for tanks is

$$P(T/v) = \frac{p(v/T)P(T)}{p(v)}\ , \tag{5}$$

and for jeeps is

$$P(J/v) = \frac{p(v/J)P(J)}{p(v)}\ . \tag{6}$$

The decision rule is: We fire if

$$P(T/v) > P(J/v)\ . \tag{7}$$

Using Equations (5) and (6), this becomes

$$P(v/T)\ P(T) > P(v/J)\ P(J)\ , \tag{8}$$

where the p(v) terms in the denominators have cancelled.

We can extend this treatment to N target types denoted by $A_i, i = 1,2 \ldots N$.

Equation (4) becomes

$$p(v) = \sum_{i=1}^{N} p(v/A_i)\ P(A_i)\quad . \tag{9}$$

We compute all the $p(v/A_i)\ P(A_i)$, and the target is classified as A_j if

$$P(v/A_j)P(A_j)\ >\ p(v/A_i)P(A_i) \text{ for all } i \neq j. \tag{10}$$

For the Gaussian distribution, the computation is simplified by taking the natural log of both sides of inequality (8), giving the decision to fire if

$$(v-\mu_J)^2\ /\sigma_J^2 - (v-\mu_T)^2\ /\sigma_T^2\ >\ C \tag{11}$$

where

$$C = 2 \ln \left\{ \sigma_J \, p(J) / \sigma_t \, P(T) \right\} \quad . \tag{12}$$

We can also introduce a predetermined "cost of decision" into the maximum likelihood classifier by defining r_{ij} as the cost ($0 \le r_{ij} \le 1$) of classifying the target as A_i when it is, in reality, A_j. For example, r_{TJ} would be the cost incurred by classifying a jeep as a tank. This cost would be higher than correctly identifying the jeep (r_{JJ}), since ammunition is wasted on a non-threat. Since identifying a tank as a jeep could be fatal, r_{JT} would be very high.

For N targets ($A_i, i = 1, 2, \ldots N$), it can be shown[2] that the cost of a decision is minimized if the target is identified as A_j by determining the minimum value of R_i, i.e.

$$R_j < R_i \quad \text{for all } i \neq j \quad , \tag{13}$$

where

$$R_i = \sum_{j=1}^{N} P(A_j) \, r_{ij} \, p(v/A_j) \quad . \tag{14}$$

For our examples of tanks and jeeps,

$$R_T = P(T) r_{TT} p(v/T) + P(J) r_{TJ} P(v/J) \tag{15}$$

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2. H.L. Van Trees, Detection, Estimation, and Modulation - Part I, John Wiley & Sons, Inc., New York, 1968.

and

$$R_J = P(T)r_{JT}p(v/T) + P(J)r_{JJ}P(v/J). \tag{16}$$

From Equation (13), the decision is made to fire if

$$P(T)r_{TT}p(v/T) + P(J)r_{TJ}P(v/J) < P(T)r_{JT}p(v/T + P(J)r_{JJ}P(v/J) \tag{17}$$

or if

$$P(T)p(v/T)\ (r_{JT} - r_{TT})\ >\ P(J)p(v/J)\ (r_{TJ} - r_{JJ})\quad . \tag{18}$$

If tanks and jeeps had the same threat potential, we would assign $v_{JT} = r_{TJ} = 1$ and $r_{TT} = r_{JJ} = 0$. Equation (18) then reduces to the previous decision rule given by Equation (8).

Now consider the possibility of using two target signatures in a maximum likelihood classifier, say radial velocities, as before, and radar cross section (RCS). Again, we measure arbitrary RCS's of tanks (N measurements) and jeeps (M measurements) under battlefield conditions and obtain mean values.

$$\mu_T' = \frac{1}{N} \sum_{i=1}^{N} (RCS)_{T_i} \quad , \quad \mu_J' = \frac{1}{M} \sum_{i=1}^{M} (RCS)_{J_i} \quad , \tag{19}$$

and standard deviations

$$\sigma_T' = \frac{1}{\sqrt{N}} \sqrt{\sum_{i=1}^{N} \left[\mu_T' - (RCS)_{T_i}\right]^2}\ , \quad \sigma_J' = \frac{1}{\sqrt{M}} \sqrt{\sum_{i=1}^{M} \left[\mu_J' - (RCS)_{J_i}\right]^2} . \quad (20)$$

We assume that the joint probability density is given by the bivariate Gaussian distribution, where the correlation between velocity and RCS is zero;[3] that is, the velocity and RCS are independent in the probability sense. The conditional joint probability can then be written as the product of two univariate Gaussian distributions, namely,

$$p(v,RCS/T) = \frac{1}{2\pi\sigma_T\sigma_T'} e^{-(v-\mu_T)^2/2\sigma_T^2} e^{-(RCS - \mu_T')^2/2\sigma_T'^2} \quad (21)$$

and

$$p(v,RCS/J) = \frac{1}{2\pi\sigma_J\sigma_J'} e^{-(v-\mu_J)^2/2\sigma_J^2} e^{-(RCS-\mu_J')^2/2\sigma_J'^2} . \quad (22)$$

This result can be extended to any number of target signatures as long as they are statistically independent. If the signatures are not independent, the multivariate Gaussian distribution must be used, and the covariances and correlations must be determined. For the case of the two signatures, velocity and RCS, assumed independent, the decision rule is: Fire if

3. Alexander M. Mood and Franklin A. Graybill, Introduction to the Theory of Statistics, McGraw Hill Book Company, Inc., New York, 1963.

$$\frac{(v-\mu_J)^2}{\sigma_J^2} + \frac{(RCS-\mu_J')^2}{\sigma_J'^2} - \frac{(v-\mu_T)^2}{\sigma_T^2} - \frac{(RCS-\mu_T')^2}{\sigma_T'^2} > C \tag{23}$$

where

$$C = 2 \ln \left(\frac{\sigma_J \sigma_J'}{\sigma_T \sigma_T'} \frac{P(J)}{P(T)} \frac{(r_{TJ} - r_{JJ})}{(r_{JT} - r_{TT})} \right) . \tag{24}$$

If we extend this result to N target types, A_i, i = 1,2, ...N, and M independent target signatures, a_i, i = 1,2, ...M, the general decision rule is: The target is A_j if

$$R_j = \sum_{k=1}^{N} P(A_k) r_{jk} p(a_1, a_2, .. a_m / A_k) < R_i = \sum_{\ell=1}^{N} P(A_\ell) r_{i\ell} p(a_1, a_2, ... a_m / A_\ell) \tag{25}$$

for all $i \neq j$. We can write

$$p(a_1, a_2, ... a_M / A_k) = \frac{1}{(2\pi)^{M/2} \prod_{i=1}^{M} \sigma_{ik}} \prod_{i=1}^{M} e^{-(a_i - \mu_{ik})^2 / 2\sigma_{ik}^2} \tag{26}$$

where

μ_{ik} is the mean of the ith signature a_i for target type A_k,

σ_{ik} is the standard deviation of the ith signature for target type A_k, and

$$\prod_{i=1}^{M} x_i = x_1 \cdot x_2 \cdot x_3 \cdot \ldots \cdot x_M \quad .$$

Then Equation (25) becomes

$$\sum_{k=1}^{N} P(A_k) r_{jk} \left(\prod_{p=1}^{M} \sigma_{pk} \right)^{-1} \prod_{p=1}^{M} e^{-(a_p - \mu_{pk})^2 / 2\sigma_{pk}^2}$$

$$< \sum_{\ell=1}^{N} P(A_\ell) r_{i\ell} \left(\prod_{q=1}^{M} \sigma_{qi} \right)^{-1} \prod_{q=1}^{M} e^{-(a_q - \mu_{q\ell})^2 / 2\sigma_{q\ell}^2} \qquad (27)$$

The flow diagram of Figure 3 shows how a maximum likelihood classifier might be implemented.

4. THE NEAREST NEIGHBOR CLASSIFIER

The nearest neighbor classifier is the least complicated (most straightforward) of the three classification techniques but also involves the most memory storage and computational load. It is a nonparametric technique in which all the training data is stored and used in classification, as opposed to the maximum likelihood method, where all the training data is reduced to three numbers per target type for each target discriminant (mean, standard deviation, and a priori probability).

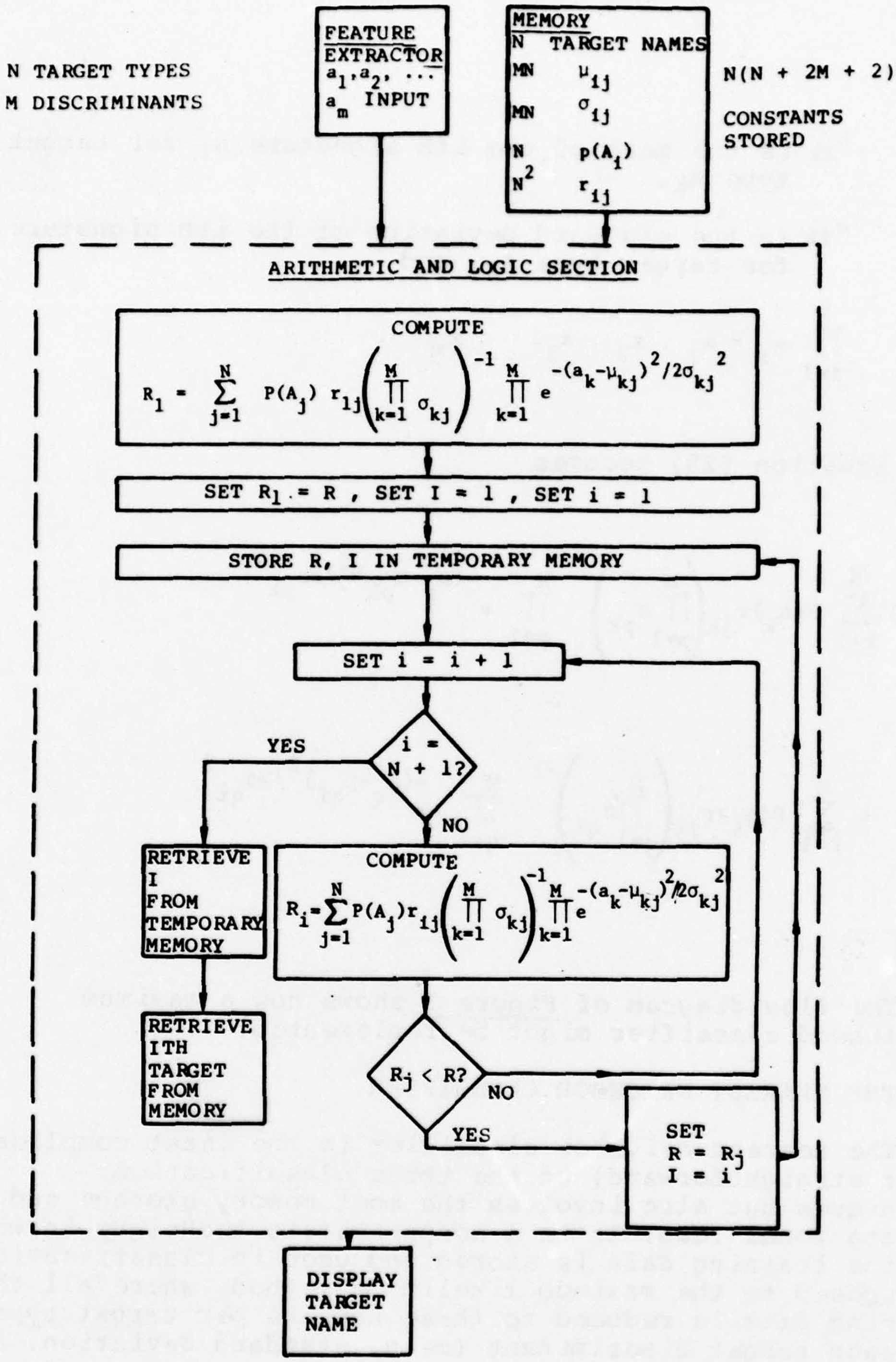

Figure 3. Maximum likelihood classifier.

Considering the same example as in the previous section, we have tanks and jeeps with radial velocity as a discriminant. The data stored in the memory consists of measured velocity values and the target observed for each value. Consider the following data taken at random in a hypothetical battlefield scenario:

Tank Velocities (mph)	Jeep Velocities (mph)
$V_1 = 2$	
$V_2 = 5$	$V_{16} = 19$
. 6	. 30
. 9	. 35
. 10	. 40
11	$V_{20} = 50$
14	
15	
16	
17	
18	
22	
. 23	
. 24	
$V_{15} = 25$	

These numbers were chosen to somewhat resemble the Gaussian distributions of Figure 2. In each memory location, we store the measured velocity v_i and the associated target type, A_k. For an unknown target with velocity v, we compute all $|v - v_i|$ and search for the minimum. If

$$|v - v_j| < |v - v_i| \text{ for all } i \neq j , \qquad (28)$$

the target is identified as the one associated with v_j. For example, if $v = 27$ mph, the "nearest neighbor" would be the tank at 25 mph. For $v = 20$ mph, the nearest neighbor is a jeep at 19 mph. This is the classical NN (nearest neighbor) rule. If we think about all of the target data being plotted on a velocity line, the nearest neighbor is the data point closest to the unknown. The a priori probabilities are taken into account by the number of tank neighbors being larger than jeep neighbors by three to one.

Clearly, a lot of data and high precision (several significant figures) are desirable. Also, one must make provisions for several targets having the same velocity. To avoid this problem, one can invoke the k-NN rule. If k is, for example, 11, the 11 nearest neighbors of the unknown target would be found. The unknown would be assigned to the majority class of these nearest neighbors; if 6 or more nearest neighbors were tanks and 5 or less were jeeps, the unknown would be classified as a tank.

One can inject the threat potential assessment into the computation by assigning a constant to each target type, v_i. Since tanks are a greater threat than jeeps, we might assign tanks a factor of $r_T = .8$ and jeeps a factor of $r_J = 1$. The decision rule (28) becomes

$$r_j \; |v - v_j| < r_i \; |v - v_i| \text{ for all } i \neq j. \qquad (29)$$

The net effect is to make tanks appear to be nearer neighbors than they actually are.

Also, one can set thresholds for decisionmaking, below which no decision is made. In the classical NN rule, one can require that the nearest neighbor be "close enough" to the unknown. For the example given, the threshold might be set at $|v - v_j| = 2$ mph. If the nearest neighbor were more than 2 mph away, the unknown would not be classified. In the k - NN rule, k = 11, one might require more than a majority, say 7 out of 11, for a decision.

Another technique which can be used is the weighted k - NN rule, in which the k nearest neighbors are weighted inversely proportional to their distance from the unclassified target. For example, we classify the target as a tank if

$$\sum_{\text{TANKS}} \left\{ \frac{1}{r_T \, |v-v_T|} \right\} > \sum_{\text{JEEPS}} \left\{ \frac{1}{r_J \, |v-v_J|} \right\} \qquad (30)$$

Provisions must be made for the computational problems resulting from $|v - v_i| = 0$.

The utility of the NN classifier becomes more apparent when extended to more than one target signature. If there are M target signatures (features), instead of being a point on a line, each training target measurement becomes a point in M-dimensional feature space. Nearest neighbors are then determined by their distance in feature space from the unknown.

Consider the two-dimensional classifier using target extent in elevation, z, and azimuth, y, determined from angular profile and range data. Plotted in two dimensions, typical training data might resemble Figure 4. For this case, the decision rule is

$$d_j < d_j \quad \text{for all } i \neq j \quad , \qquad (31)$$

or

$$\sqrt{(y-y_j)^2 + (z-z_j)^2} < \sqrt{(y-y_i)^2 + (z-z_i)^2} \quad . \qquad (32)$$

Although it is not readily apparent from this example, this simple formulation is flawed in that it tends to weight one feature more heavily than another. For example, targets are generally longer than they are high, but not necessarily

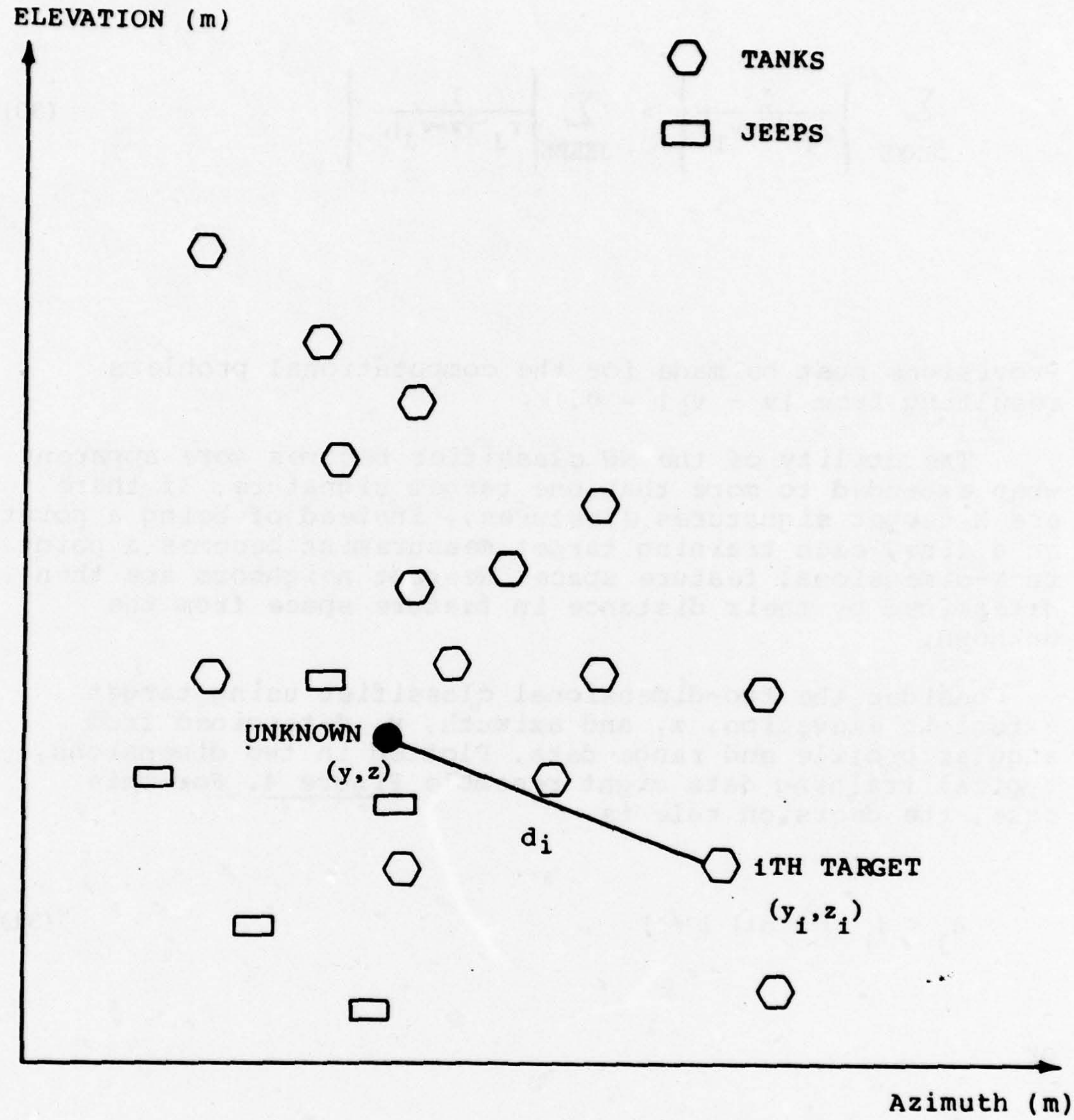

Figure 4. Target extent training data.

wider. Thus, because of variations in yaw aspect angle, we expect a large range of values for the y_i and a small range for the z_i. Thus, the $(y-y_i)^2$ terms will dominate over the smaller $(z-z_i)^2$ terms. This disparity becomes more visible if we use as features: (1) the radial velocity, which perhaps varies between ~ 5 mph and ~ 50 mph; and (2) RCS which might vary between 5 m^2 and 500 m^2. If we use Equation (32), the RCS will dominate over the velocity.

Clearly, some form of "normalization" depending on the spread of data will probably be needed. We can "normalize" by dividing each feature by the sample standard deviation for the target signature y given by

$$\sigma_y = \frac{1}{\sqrt{n}}\sqrt{\sum_{i=1}^{n} (y_i - \mu_y)^2} \tag{33}$$

where n = total number of training samples and μ_y is the sample mean given by

$$\mu_y = \frac{1}{n} \sum_{i=1}^{n} yi \quad . \tag{34}$$

The decision rule then becomes

$$\sqrt{\left(\frac{y-y_i}{\sigma_y}\right)^2 + \left(\frac{z-z_i}{\sigma_z}\right)^2} < \sqrt{\left(\frac{y-y_j}{\sigma_y}\right)^2 + \left(\frac{z-z_j}{\sigma_z}\right)^2} \quad \text{for all } i \neq j. \tag{35}$$

For an M-dimensional feature space (M types of target signatures), x_{ki}, k = 1,2 . . M, where i denotes the ith target and x_k is the unknown, the decision rule is

$$\sqrt{\sum_{k=1}^{M}\left(\frac{x_k - x_{kj}}{\sigma_{x_{kj}}}\right)^2} < \sqrt{\sum_{k=1}^{M}\left(\frac{x_k - x_{kj}}{\sigma_{x_{kj}}}\right)^2} \quad \text{for all } i \neq j. \qquad (36)$$

The implementation of the NN classification is similar to that shown in Figure 2, except that the computation loop is traversed n times (n = total number of training samples) instead of only N times (number of target classes). Modifications needed to implement the k - NN rule and the weighted k - NN rule will result in an additional computational load. In addition, memory requirements have increased to nM + 2MN + N, where nM is the number of sample data, 2 MN is the number of means and standard deviations, and N is the number of weighting (threat) factors.

It should be pointed out that there are many variations of the NN classifier which have not been discussed. These include techniques for reducing the size of the training data set and computational tricks to increase processing speed.[4]

5. THE LINEAR CLASSIFIER

With the maximum likelihood classifier, a complete knowledge of the probability distribution of the target signatures was assumed, and this assumption resulted in small computational loads. In the NN classifier, essentially nothing was assumed, and memory and computation requirements were large. The linear classifier is a nonparametric technique with assumptions about the distribution and field computational loads lying somewhere between the extremes of the maximum likelihood classifier and nearest neighbor classifier.

The assumption made in the linear classifier is that the target classes can be separated in multidimensional feature space by discriminant surfaces called hyperplanes. To understand what the previous statement means, consider the

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4. B.V. Dasarathy, A Study of Nearest Neighbor Classification Techniques in the Context of Millimeter Radar Target Recognition and Selection Applications, M&S Computing, Inc., Report No. 78-017, March 1978.

two feature case of Figure 5a where the discriminants are measured target extent in elevation and azimuth. In this case, the "hyperplane" is a line. We assume that we can find the equation for a straight line that separates all the tanks from all the jeeps, so that any unknown can be classified on the basis of on which side of the line it falls. In fact, we assume that even when no straight line exists that separates the data, we can apply an algorithm to the data which will give us the "best" line, i.e., the line that will give us the least probability of misclassification.

We now add target extent in range to elevation and azimuth extent, so that we have a three-dimensional feature space, as shown in Figure 5b. In this case the hyperplane is a plane separating the targets in space. If we extend this treatment to M types of target signatures, x_i, i = 1, 2, 3, . . . M, the discriminant surface is a "hyperplane" in M-dimensional space.

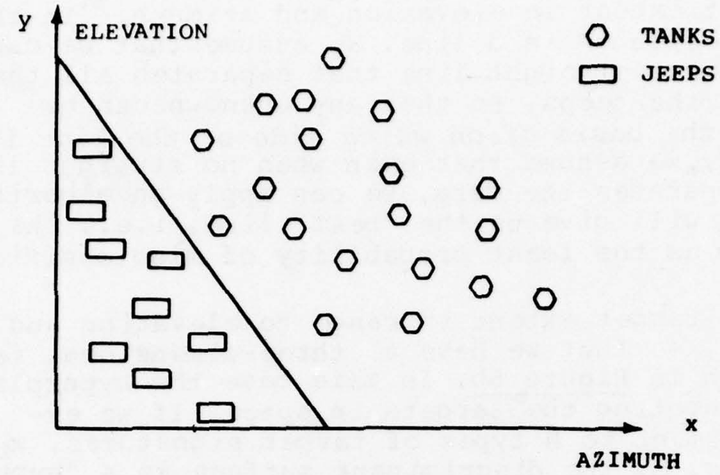
Considering now the treatment of three or more target classes (number of classes = N), we have the option of trying to find a discriminant surface for each class which separates that class from all others, or we can find surfaces which separate each pair of classes. The first case requires N hyperplanes, resulting in a small computational load for determining unknowns, but the linear separability assumption is likely to be less valid.

The latter case requires 1/2 N (N -1) hyperplanes and more computations to determine unknowns. However, it often gives a higher accuracy, because a given target class is more likely to be linearly separable from each class individually than from all other classes lumped together.

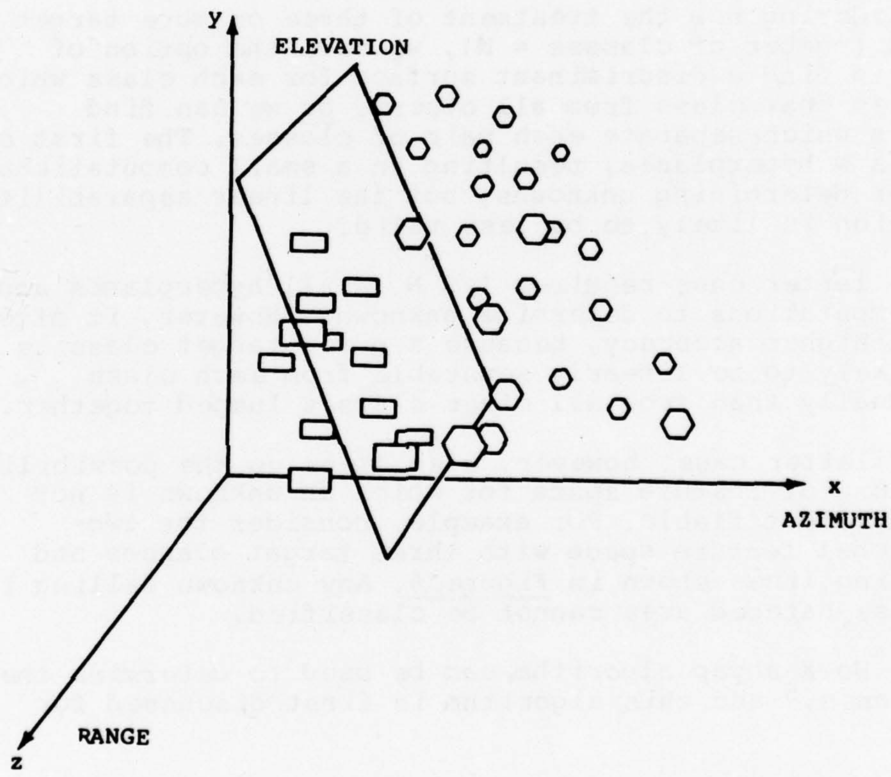
The latter case, however, also opens up the possibility of regions of feature space for which an unknown is not uniquely identifiable. For example, consider the two-dimensional feature space with three target classes and separating lines shown in Figure 6. Any unknown falling in the cross-hatched area cannot be classified.

The Ho-Kashyap algorithm can be used to determine the hyperplanes,[5] and this algorithm is first discussed for

5. Yu-Chi Ho and R.L. Kashyap, "A Class of Iterative Procedures for Linear Inequalities," J. SIAM Control, Vol. 4, 1966, pp. 112-115.



a.



b.

Figure 5. Target extent training data.

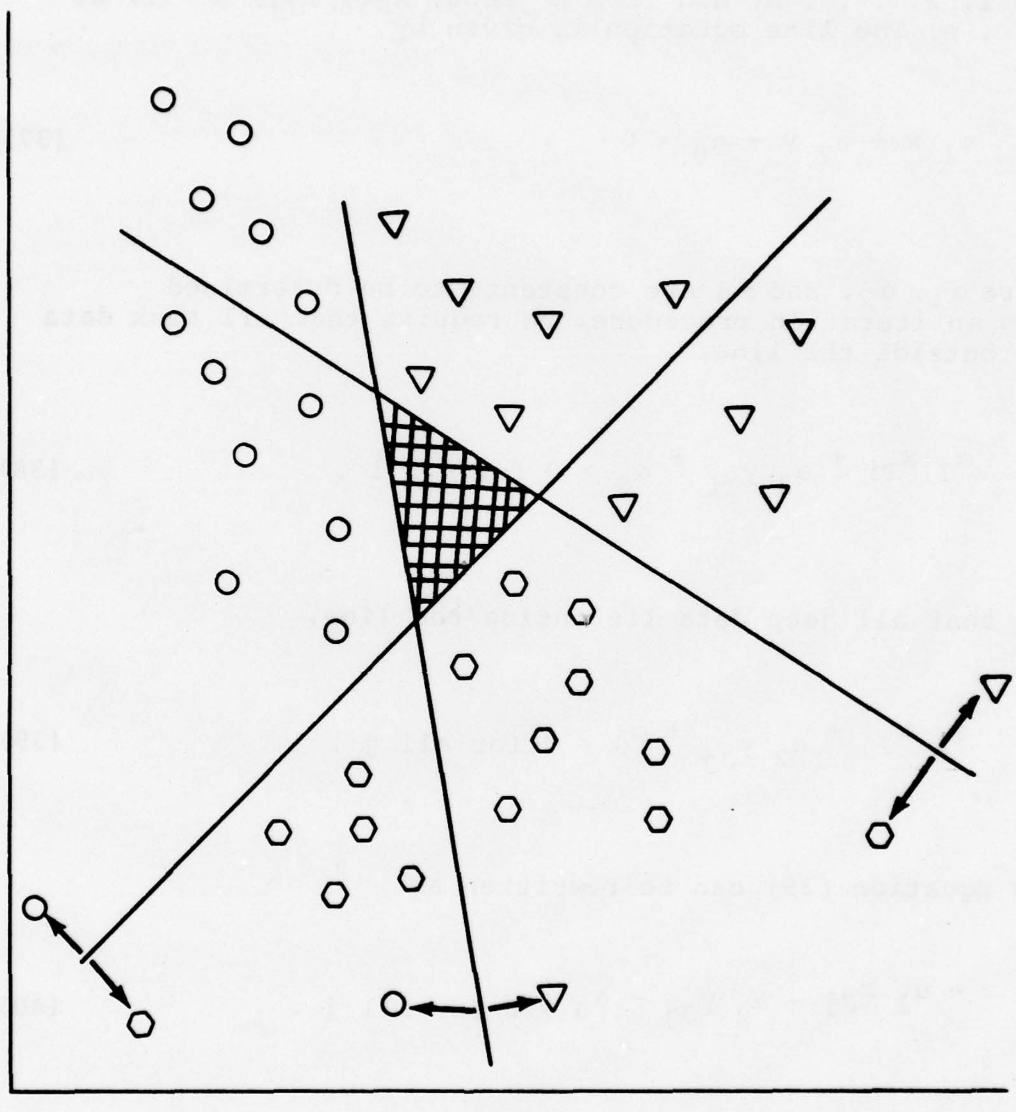


Figure 6. Ambiguity in two-dimensional feature space.

two target discriminants: extent in azimuth (x) and elevation (y) as in Figure 5a. (The x_i and y_i are normalized as before.) We wish to find the straight line that separates measurements obtained from m tanks x_{Ti}, y_{Ti}, i = 1, 2, . . . m, and from n jeeps, x_{Jj}, y_{Jj}, j = 1, 2, . . . n. The line equation is given by

$$\alpha_1 x + \alpha_2 y + \alpha_0 = 0 \tag{37}$$

where α_1, α_2, and α_0 are constants to be determined from an iteration procedure. We require that all tank data lie outside the line,

$$\alpha_1 x_{Ti} + \alpha_2 y_{Ti} + \alpha_0 > 0 \text{ for all } i , \tag{38}$$

and that all jeep data lie inside the line,

$$\alpha_1 x_{Jj} + \alpha_2 y_{Jj} + \alpha_0 < 0 \text{ for all } j . \tag{39}$$

Now Equation (39) can be rewritten as

$$- \alpha_1 x_{Jj} - \alpha_2 y_{Jj} - \alpha_0 > 0 \text{ for all } j . \tag{40}$$

Thus we have n + m linear equations which may be written in matrix form as

$$\begin{bmatrix} x_{T1} & y_{T1} & 1 \\ x_{T2} & y_{T2} & 1 \\ \vdots & \vdots & \vdots \\ x_{Tn} & y_{Tn} & 1 \\ -x_{J1} & -y_{J1} & -1 \\ -x_{J2} & -y_{J2} & -1 \\ \vdots & \vdots & \vdots \\ -x_{Jm} & -y_{Jm} & -1 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_0 \end{bmatrix} > \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \qquad (41)$$

or

$$\underline{A}\,\alpha > 0 \ . \qquad (42)$$

We introduce the variable vector $\beta = (\beta_1, \beta_2, \dots \beta_n, \beta_{n+1}, \dots \beta_{n+m})$ such that we must find β for which

$$A\ \alpha - \beta = 0 \qquad (42)$$

and

$$\beta > 0 \ . \qquad (43)$$

"The introduction of the vector $\boldsymbol{\beta}$ as an additional variable plays a crucial role in the convergence rate of the algorithm without any appreciable increase in computational complexity."[5] Before convergence, $A\ \alpha - \beta \neq 0$, so we introduce the vector γ defined by

$$\gamma = A\ \alpha - \beta \ . \qquad (44)$$

We also introduce the scalar constant ρ and the symmetric matrix S (in this case S is a 3 x 3 matrix). One possible choice of ρ and S are

$$0 < \rho < 2 \tag{45}$$

$$S = (A^T A)^{-1} \tag{46}$$

where A^T is the transpose of A,

$$A^T = \begin{bmatrix} x_{T1} & x_{T2} & \cdots & x_{Tn} & -x_{J1} & -x_{J2} & \cdots & -x_{Jm} \\ y_{T1} & y_{T2} & \cdots & y_{Tn} & -y_{J1} & -y_{J2} & \cdots & -y_{Jm} \\ 1 & 1 & \cdots & 1 & -1 & -1 & \cdots & -1 \end{bmatrix} \tag{47}$$

and

$$A^T A = \begin{bmatrix} \begin{pmatrix} x_{T1}^2 + x_{T2}^2 + \cdots x_{Tn}^2 \\ + x_{J1}^2 + x_{J2}^2 + \cdots x_{Jm}^2 \end{pmatrix} & \begin{pmatrix} x_{T1}\, y_{T1} + x_{T2}\, y_{T2} + \cdots x_{Tn}\, y_{Tn} \\ + x_{J1}\, y_{J1} + \cdots\cdots \quad x_{Jm}\, y_{Jm} \end{pmatrix} & \begin{pmatrix} x_{T1} + x_{T2} + \cdots x_{Tn} \\ + x_{J1} + x_{J2} + \cdots x_{Jm} \end{pmatrix} \\ \begin{pmatrix} x_{T1}\, y_{T1} + \cdots x_{Tn}\, y_{Tn} \\ + x_{J1}\, y_{J1} + \cdots x_{Jm}\, y_{Jm} \end{pmatrix} & \begin{pmatrix} y_{T1}^2 + y_{T2}^2 + \cdots y_{Tn}^2 \\ + y_{J1}^2 + y_{J2}^2 + \cdots y_{Jm}^2 \end{pmatrix} & \begin{pmatrix} y_{T1} + y_{T2} + \cdots y_{Tn} \\ + y_{J1} + y_{J2} + \cdots y_{Jm} \end{pmatrix} \\ \begin{pmatrix} x_{T1} + x_{T2} + \cdots x_{Tn} \\ + x_{J1} + x_{J2} + \cdots x_{Jm} \end{pmatrix} & \begin{pmatrix} y_{T1} + y_{T2} + \cdots y_{Tn} \\ + y_{J1} + y_{J2} + \cdots y_{Jm} \end{pmatrix} & \begin{pmatrix} n + m \end{pmatrix} \end{bmatrix} . \tag{48}$$

S is then the inverse of the $A^T A$, which is found from the determinants of the cofactors and the matrix determinant.

It can be shown that the algorithm

$$(\alpha)_{i+1} = (\alpha)_{i+\ell}\, S\, A^T \,|\gamma_i|\ ,\ \alpha_0 \text{ arbitrary,} \tag{49}$$

$$(\beta)_{i+1} = (\beta)_i + (\gamma_i + |\gamma_i|), \beta_0 > 0 \text{ but arbitrary otherwise} \tag{50}$$

converges to the solution of $A\,\alpha - \beta = 0$ in a finite number of steps provided a solution exists. The subscripts here denote the number of iterations performed. Initially we choose ρ, $(\alpha)_0 = \{(\alpha_1)_0, (\alpha_2)_0, (\alpha_0)_0\}$, and $(\beta)_0 = \{(\beta_1)_0, (\beta_2)_0, + \ldots (\beta_{n+m})_0\}$, plug these into Equation (44) and compute

$$\gamma_0 = A\,(\alpha)_0 - (\beta)_0 \quad . \tag{51}$$

Then, using Equations (49) and (50), compute

$$(\alpha)_1 = (\alpha)_0 + \rho\, S\, A^T\, |\gamma_o| \tag{52}$$

and

$$(\beta)_1 = (\beta)_0 + (\gamma_0 + |\gamma_0|) \quad . \tag{53}$$

Returning to Equation (44), we find γ_1 :

$$\gamma_1 = A\,(\alpha)_1 - (\beta)_1 \tag{54}$$

and continue the precedure until $\gamma_i \to 0$.

Now if there is no solution (i.e., the tank and jeep data overlap so that the discriminant line does not exist), we can continue the iteration process until the $(\alpha)_i$ do not change very much from one iteration to the next. For example, we might stop at the 76th iteration, provided we have a one percent accuracy:

$$\frac{(\alpha_j)_{76} - (\alpha_j)_{75}}{(\alpha_j)_{75}} < .01 \text{ for } j = 0,1,2 \tag{55}$$

where the α_j are the components of the vector α.

It is clear that even for the case of the two target types and two discriminants, the computation of the α_1, α_2, and α_0 for Equation (37) is quite involved and normally needs to be done on a main frame computer. However, once these three constants are determined, they are all that needs to be stored in the field microprocessor. If we measure x and y for an unknown, the target is identified as a tank if

$$\alpha_1 x + \alpha_1 y + \alpha_0 > 0 \ . \tag{56}$$

Now consider the problem for two target types and M types of target signatures x_i, i = 1,2, . . . M. The computation of the M + 1 constants (α_1, α_2, . . . α_m, α_0) is considerably more difficult because the vectors involved now have M + 1 components and the matrix S is now (M + 1) X (M + 1). The computational and storage

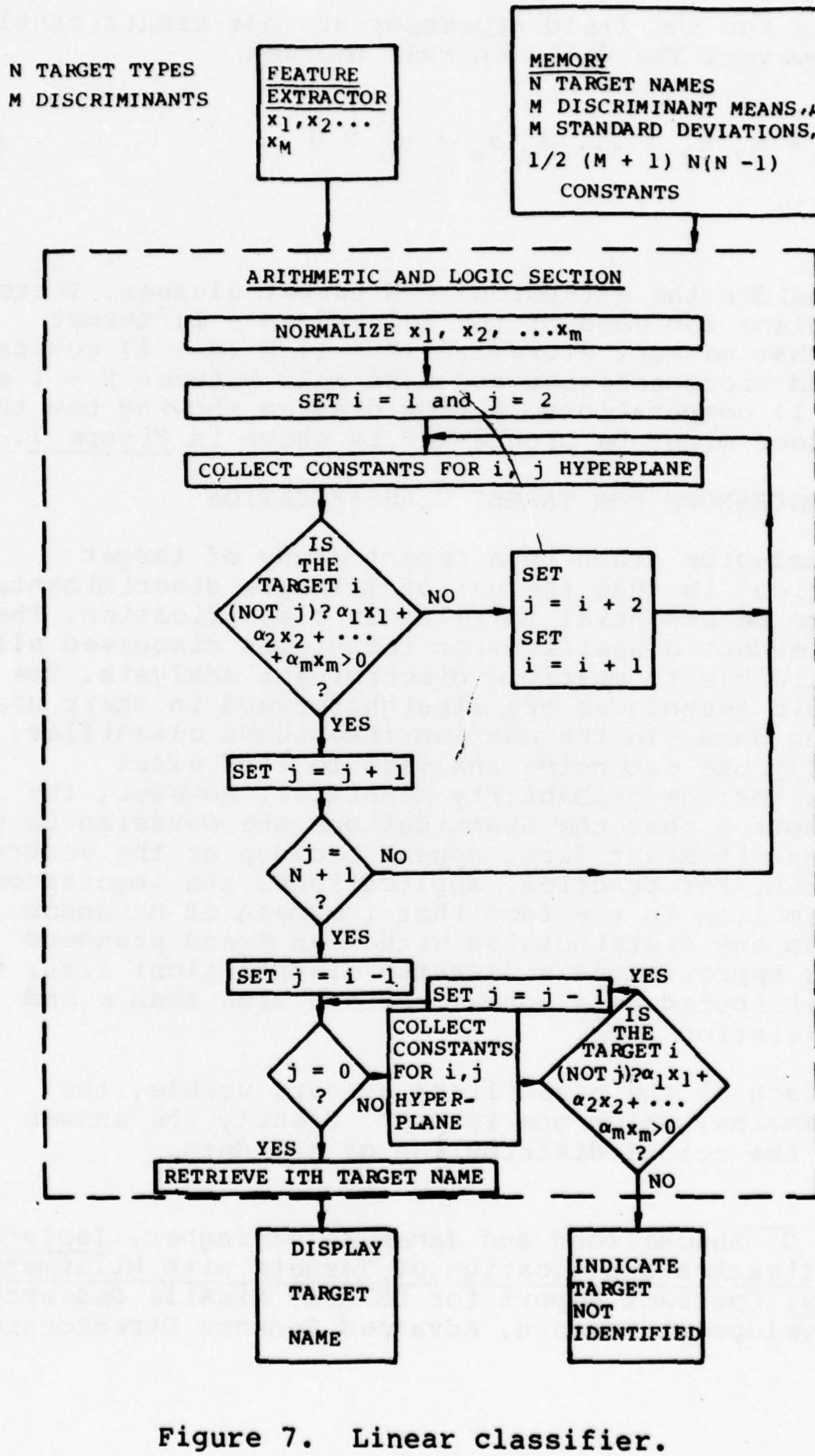


Figure 7. Linear classifier.

requirements for the field processor are not significantly altered, however. The decision rule becomes

$$\alpha_1 x_1 + \alpha_2 x_2 + \ldots \alpha_m x_m + \alpha_0 > 0 \quad . \tag{57}$$

Now consider the extension to N target classes. There will be a plane for each of the 1/2 (N) (N - 1) target pairs, so that we must store 1/2 (M + 1) N (N - 1) constants in the field microprocessor and must make between N - 1 and 1/2 N (N - 1) computations. A flow diagram showing how the microprocessor might be programmed is shown in Figure 7.

6. MICROPROCESSORS FOR TARGET CLASSIFICATION

One conclusion drawn in a recent study of target classification[6] is that the use of multiple discriminants is likely to be essential to reliable classification. The three independent classification techniques discussed all appear applicable to multiple discriminant analysis. The nonparametric techniques are straightforward in their use of the training data. In the maximum likelihood classifier, one would ideally use extensive analysis to find exact expressions for the probability densities. However, the basic assumption that the distributions are Gaussian is more credible than it might first appear because of the central limit theorem. For practical applications, the importance of this theorem lies in the fact that the mean of n random samples from any distributuion with mean μ and standard deviation σ approximates a Gaussian distribution; i.e., the mean is distributed as a normal variate with mean μ and standard deviation $\sigma|\sqrt{n}$.

While each of the classifiers appears usable, the question remains, which one is best? Clearly the answer depends on the actual distribution of the data.

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6. Robert G. Shackelford and James J. Gallagher, Isolation, Classification and Location of Targets with Millimeter Systems, Contract Report for US Army Missile Research and Development Command, Advanced Sensors Directorate, 1978.

Dasarathy,[1] in a preliminary effort, has compared the three techniques using artificially generated data for target extent in azimuth, elevation, and range. He found no significant differences in the recognition rates for the classifiers. Naturally, the results of any simulation will depend heavily on how the test data is generated, so that actual data will be required for any final rating of the classifiers.

To assess the applicability of microprocessors to field classification, consider the case for five target types and five target discriminants. Since we might expect that no classification improvements result from training data less than 1 degree apart in aspect angle,[6] let us (assuming some target symmetry) take n, the total number of training samples, to be 900, or an average of 180 samples per target. The number of constants stored in the microprocessor are 75 for the linear classifier, 85 for the maximum likelihood classifier, and 4,555 for the nearest neighbor classifier. The point of these results is that, as far as computation and memory requirements are concerned, if one is going to use the linear classifier, one might as well also use the maximum likelihood classifier (and vice versa); and if one is going to use the nearest neighbor technique, one might as well use all three classifiers. The use of some combination of the classifiers would seem optimum, since if neither of the faster classifiers (maximum likelihood and linear classifiers) gave a firm decision, the NN classifier would be available. Otherwise, one could use a majority rule, or a weighted majority rule if the classifiers could be rated according to their expected performance.

A microprocessor to be used in such a classification system would require a reasonably large permanent memory for the storage of constants and computation programs, but a relatively small temporary memory. Temporary memory is usually referred to as RAM (random access memory), which provides immediate access to all memory storage locations. The permanent memory is called the ROM (read only memory) which may be programmed by a mask pattern in the last manufacturing stage or may be programmed in the field using suitable equipment. In the latter case, the memory is called a PROM (programmable read only memory). Program data stored in the ROM cannot be altered and for that reason is often called firmware. Memory storage is measured in bytes (computer words) usually of 4 or 8 bits (one bit = one on-off switch).

There are currently available single board microcomputers (Motorola, Texas Instruments, Zilog, etc.) which provide 8 k byte PROM capacity (k = 1,024) and from 512 to 4 k of RAM, all at a nominal cost of $300 (for a quantity of 100). The PROM capacity would appear to be adequate for the example given, since 3,477 bytes would be left for program instructions after the storage of 4,715 constants.

7. SUMMARY AND CONCLUSIONS

This report addresses the subject matter in a highly fundamental manner. The basics of the three classifiers have been presented, but no attempt has been made to consider other classification techniques nor to expand on the three classifiers discussed. An obvious extension of the computerized classifier is one which continually updates the data base as targets are successfully identified in the battlefield. It has been shown, however, that there exist three classification techniques which can be easily implemented to experimental data from mm wave radars.

To implement the maximum likelihood classifier, one makes a broad assumption about the training data and boils the data down to very few numbers; the result is low memory storage and very few computations needed for classification. The validity of the Gaussian assumption is questionable but is given some credence as a result of the nature of random variables.

In the nearest neighbor classifier, no assumptions are made, and all of the training data is retained. Many repetitive but simple computations must be performed to classify a target.

As a result of extensive preprocessing of the data, the linear classifier requires low memory storage and has a computation load intermediate between the nearest neighbor and the maximum likelihood classifier. Although the calculation of the constants representing the discriminant hyperplanes is complex, the use of these constants in the field classifier is straightforward.

It has also been shown that currently available microprocessors have sufficient capabilities to implement the classifiers for field radar systems. It is felt that the small size, high computing power, and low cost of

microprocessors will dictate their use in millimeter wave target acquisition systems.

Finally, it is concluded that a program needs to be carried out to integrate a microprocessor into an experimental mm wave radar system to allow an evaluation of the various target signatures and classifiers. Experimental target signature data are required to effectively assess the utility of the classification techniques.

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